Short-Term Persistence in Norwegian Equity Mutual Funds

Dag Skreden

Department of Economics, Norwegian University of Science and Technology (NTNU)

May 2012

Abstract

In order to analyze short-term persistence in Norwegian equity mutual fund returns, two methods are applied. The backbone for both of them is a sorting procedure that creates four equally weighted portfolios based on lagged one-year returns. These ranked portfolios are subject to three different holding strategies, i.e. they are rebalanced every one, six and twelve months. The first method uses the 4-factor model by Carhart to obtain risk-adjusted returns from all the portfolios. The second one analyzes rank dependency by utilizing contingency tables. The results are somewhat mixed. None of the ranked portfolios were able to create significant risk-adjusted alphas, but simple returns seem to be affected by rankings and the holding periods. Consistency in rankings is present when the portfolios are rebalanced every one and six months. Finally, persistent behavior is gradually diminishing as the post-formation period increases.

Preface

This thesis represents the end of my MSc in Financial Economics at NTNU. During the course of this education, I have gained a genuine interest in asset returns and how they behave in the ever-evolving financial markets. I have therefore chosen this to be the main focus in the forthcoming analysis.

I would like to thank my supervisor Hans Marius Eikseth for valuable comments and Eivind Sars Veddeng for proofreading. Furthermore, I would like to thank Morningstar Norway for providing me with necessary data.

Dag Skreden
Trondheim, 3rd of May, 2012

Table of Contents

List of Tables

List of Figures

1 Introduction

Financial markets around the world have experienced periods of severe turmoil during the past century, where the recent financial crisis of 2008 serves as the biggest negative shock since the Great Depression. Massive corrections took place in several markets after this event, especially in developed economies like the U.S. and the Eurozone. This has unquestionably increased the focus on the returns of equity assets such as mutual funds and their underlying stocks. In these periods of high volatility, uncertainty tends to affect the risk appetite of private and institutional investors. Some will naturally shift their exposure to less risky assets to get safer returns on their capital. However, as markets plummet, key policy rates tend to go down as governments try to stimulate economies during recessions. This will from time to time create a negative real rate of return on traditional low risk investments, making well-diversified mutual funds look like more profitable investments over time.

It seems to be a growing consensus around the globe that mutual funds, on average, create higher returns than for instance a standard savings account. That is if the investment horizon is relatively long. This has unsurprisingly become one of the industry's favorite arguments when campaigning for their products, i.e. mutual funds. Such marketing strategies have been criticized heavily by the academic world. The notion that you can get higher expected returns "for free" by changing exposure to other assets is not supported by financial theory where free lunches in general does not exist. As economists have pointed out for decades, consistent high returns compared to some benchmark must be a product of higher risk. In practice, investors choose to take on more risk in order to get the increased expected return in the form of a risk premium. This gives major implications against using gross returns as an argument for performance. High returns could simply be the case of high risk. Academics have therefore found ways to create risk-adjusted returns so that an asset would need to create higher returns relative to the risk it bears in order to receive any credit. A variety of research papers have analyzed the mutual fund industry's ability to create risk-adjusted returns over the years, e.g. Jensen (1968) and the more recent Fama and French (2010). The conclusions have mostly been devastating for the fund managers. Very few funds seem to be able to create better returns than the underlying theory would predict. This has by no means stopped the industry from using gross returns as their parameter of choice when introducing funds to the public.

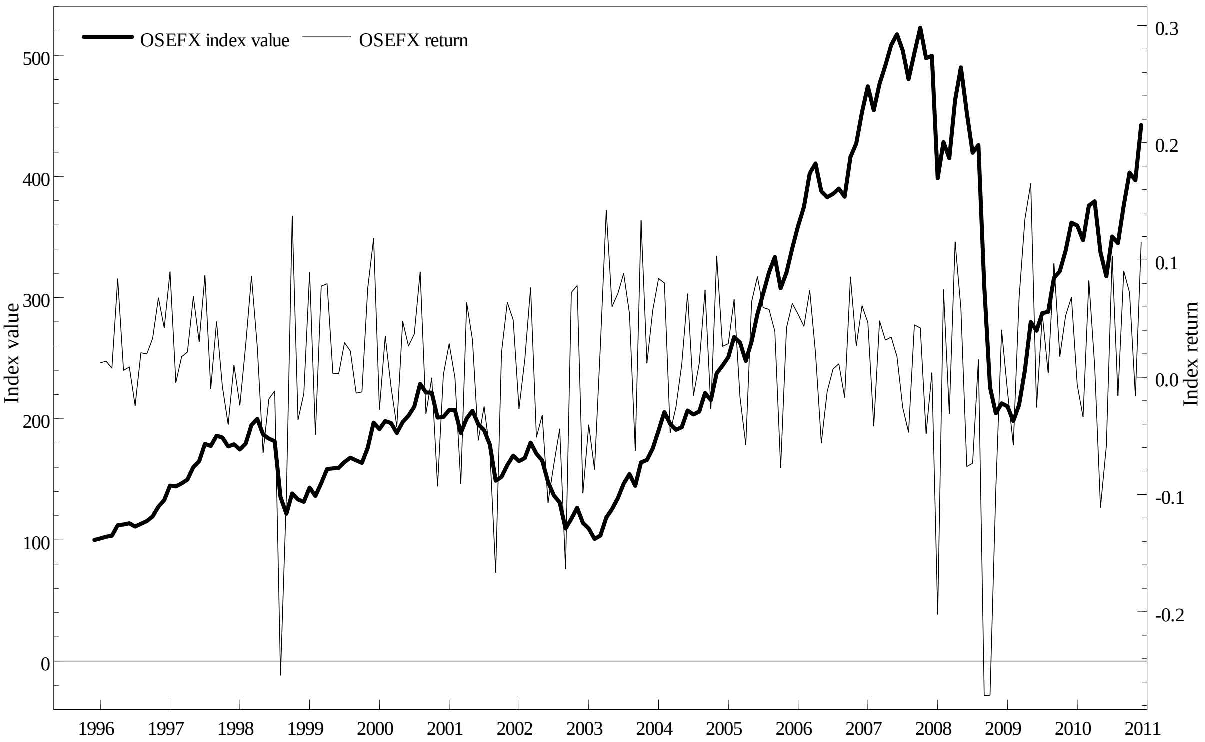

Figure 1: Index values and monthly returns of the Oslo Børs Mutual Fund Index

This type of marketing presents another problem, which will be the main topic of this thesis. The intuitively appealing thought that high previous returns will lead to high future returns is at best questionable in the light of financial theory. Nevertheless, past returns are often used in practice as an indicator of expected returns. These types of momentum strategies center their trading profiles on persistence in mutual fund returns. Much research has been done on this matter for the U.S. market, e.g. Malikel (1995) and Carhart (1997), but the results are slightly mixed. However, the general opinion is that most funds do not exhibit persistent behavior, at least in a risk-adjusted world. The latest paper describing persistence in Norwegian mutual funds is Sørensen (2009). He found no sign of significant persistence in returns, but his analysis on this matter covers only one operational method, and it represents a minor part of the overall paper.

The problem addressed by this thesis is to what extent Norwegian equity mutual funds display persistent behavior in returns. The analysis wants to enlighten this problem by using a methodology similar to the one applied by Carhart (1997), but it will implement it in a somewhat different manner.

It all begins with defining three different trading strategies that will work as a foundation in the analysis. Funds are first ranked according to their lagged one-year returns and put into four portfolios based on these rankings. Then, all portfolios are reformed every one, six and twelve months, which works as three holding strategies. The purpose of this is to look at how portfolio returns change as the post-formation period increases. These returns are finally regressed against the 4-factor model of Carhart (1997) to obtain risk-adjusted returns. If one of the top or bottom portfolios in fact exhibit abnormal returns, then it would question the efficiency of the respective market as it introduces a trading pattern that can easily be implemented in real life.

As a second act, consistency in rankings is analyzed. Contingency tables, similar to the one by Carhart (1997), are constructed for each holding strategy. These represent the historical probabilities of ending in one ranking given an initial ranking. The advantage of such an approach is that patterns of persistent behavior are much more visible than before. Three charts display these properties over the different holding periods. This method says nothing about how big the underlying returns are, but it gives a picture of how previous returns have affected future returns relative to the other ranked portfolios.

The analysis finds no sign of persistent risk-adjusted returns across the portfolios. This means that none of the holding strategies are able to create significant abnormal returns during the sample period. This indicates no real threat towards the market efficiency of the Norwegian equity fund market. As to rank dependency, substantial differences are observed between the three strategies. Persistent behavior in rankings is strong when the holding period is one month, while it diminishes considerably as the period is set to six months. The pattern of persistence is for all practical purposes wiped out when the twelve month holding period is applied.

A summary of relevant theory and research marks the beginning of this thesis in the second section. This is followed by the methodology used in the analysis. A full data description will then explain all relevant parameters and present the descriptive statistics of interest. The ending includes final results and concluding remarks.

2 Historical Background

Short-term persistence is the subject of interest in this thesis, but in order to create a picture of this, a measure of performance is needed. The first subsection will therefore present the evolution of some performance methods, while the second introduces the historical findings on persistence. The third and final part will work through the efficient market hypothesis and relate it to persistence in asset returns.

2.1 Measuring Performance

The literature on this subject is extensive and it is outside the scope of this thesis to cover it all. The focus will be on the factor models of Jensen (1968), Fama and French (1993) and Carhart (1997). Ratio measures have also been widely used in mutual fund performance research. Sharpe ratio, Treynor ratio, Information ratio and M^2 are perhaps the most common of them. Their popularity may be a product of their intuitive nature and the fact that they are quite easy to construct. The different ratios are all risk-adjusted measures. They do however implement this in different ways.

The chase for good performance measures is an ongoing process. More complex procedures are constantly being brought to the table. Dynamic benchmarking is one of those. State dependent variables, in addition to the regular passive factors (RMRF, SMB etc.) can be used to measure the performance of a mutual fund. The time varying variables could reflect macro factors like interest rate spreads or credit rating spreads.

2.1.1 CAPM and Jensen's α

It is natural to start with the Capital Asset Pricing Model (CAPM) credited to Sharpe (1964) and Lintner (1965), which serves as a building block for the other performance models. According to Cochrane (2005) it is the first, most famous and the most widely used model in asset pricing. It was very successful for a long time and it fitted empirical data well, so its popularity is no mystery. The key principle of this equilibrium model is that an asset's return depends solely on the risk-free rate and its correlation with the market portfolio. Thus, the only source of risk is its exposure towards the market. The expected return of an asset is then positively correlated with its covariance with the market. This means that an asset can only achieve higher expected returns by increasing its systematic risk.

Jensen (1968) pulled the CAPM into a performance setting for equities like mutual funds. The CAPM tells us what a mutual fund is expected to earn given its systematic risk. So for a mutual fund to exhibit performance out of the ordinary, it would have to produce a higher rate of return than the theory would predict. This abnormal return is measured by the estimated intercept in the model given by equation (1) in the methodology section. The famous alpha is then the estimated intercept.

2.1.2 Fama and French 3-Factor Model

Even though the CAPM worked well for many years, anomalies continued to shake its foundation. One of these was the small firm effect discovered by Banz (1981). He found that firms with smaller market capitalization tended to give higher returns than the CAPM would predict. Fama and French (1993) constructed a variable based on this pattern called the SMB (small minus big). Another characteristic that broke with the CAPM equilibrium was the value effect. Stocks with a high book-to-market ratio (value stocks) seemed to earn positive abnormal returns, while stocks with a low book-to-market ratio (growth stocks) underperformed. This resulted in the variable HML (high minus low). These two factors are supposed to mimic an underlying and undiversifiable risk that explains the cross-sectional returns that are not accounted for by the CAPM. The reasoning of implementing the additional variables is quite similar to the well-known market factor in the CAPM. Higher returns must be a product of higher risk. Therefore, when small-cap and value stocks over time outperform their counterparts, it must be because of some underlying risk that investors cannot simply diversify away.

No absolute answer is given by Fama and French on what this risk that affects economic fundamentals really is. They do however come up with some plausible ideas. One of them is that the market price of a typical value firm has recently been declining due to bad news, and is close to bankruptcy. These firms have historically come back more often than not, hence the abnormal returns. As to risk, firms in financial distress will tend to do very bad in times where the market has turned sour. This is therefore a type of stock that performs very poorly when the overall investor needs it the most. This give reasons to label them with a higher risk premium. An explanation like this is one out of many and it is still no general consensus on the risk interpretation.

Although the model lacks a strong theoretical foundation, it has performed very well in the task of explaining asset returns. The R^2 of Fama and French's regressions are near 90%, which is much higher than what the CAPM could explain.

2.1.3 Carhart 4-Factor Model

The momentum factor of Jegadeesh and Titman (1993) is not captured by the 3-factor model. In this paper, they find that an investment strategy of buying past winners and selling past losers yields significant abnormal returns. They blame this partially on delayed reactions on new information, but emphasizes that further research on investor behavior is needed to give an absolute conclusion. The risk perspective behind this factor is perhaps even more controversial than the Fama and French factors. A theoretical substance is missing and plausible explanations are at best questionable.

Although there is no easy risk interpretation of this factor, some trends indicate that momentum based trading contains extra risk. Looking at Figure 5, we see that PR1YR returns for the Norwegian market plummet during the turmoil of the recent financial crisis. This factor is simply the returns of going long in previous top performers and short in the previous bottom performers. A similar trend can be observed for the U.S. momentum factor obtained from the webpage of Kenneth R. French.[1] Figure 13 in the appendix clearly shows two distinctive downturns, one during the Great Depression, the other one during the financial crisis of 2008. An investor should demand an extra risk premium for holding assets that perform poorly in times of economic distress. If assets that are exposed to the momentum factor systematically underperform when the overall economy goes bust, then they should be given a risk premium like the 4-factor model does. The problem of explaining why these assets potentially are more risky than others remains unsolved.

Carhart (1997) includes a variable that reflects this anomaly and it is a direct extension of the 3-factor model. He states in his paper that the attachment of the momentum variable, PR1YR (prior one year), extensively improves the explained variation of cross-sectional returns relative to the CAPM and the 3-factor model. This eliminated almost all of the pricing error patterns in his sample, which indicates that the new variable works with explaining asset returns. Again, the estimated intercept of the regression serves as the measure of performance.

[1] http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/index.html

2.2 Research on Persistence

This issue has also been a subject of extensive research. Persistence gives rise to a rather unsophisticated, but commonly used investment strategy of buying past winners. This might explain some of its popularity as a field of interest. Mutual fund managers are still depending heavily on historical returns when marketing their funds. Thus it seems like investors, to some extent, make their investment decision based on how well a fund has performed in the past. So the question many researchers have asked is whether top performers continue their success, or is it just a matter of random chance.

Malikel (1995) takes on the U.S. fund market from 1971 to 1991 and looks at the “hot hand” phenomenon, i.e. if funds that perform above average continue to do so. He uses a methodology where he sorts portfolios based on their performance relative to the median. Funds that achieve a higher (lower) rate of return get labeled as winners (losers). The paper concludes that hot hands are present in the 1970s, but the pattern seems to disappear in the 1980s. This is further confirmed when the author simulates trading strategies based on persistence. They yield excess returns in the first decade, but struggles to follow up in the subsequent. Persistence is therefore present in the sample, but it is not robust. Similar results can be found in a variety of papers that analyze the U.S. mutual fund market.

A different approach is used in the highly influential paper by Carhart (1997). A more detailed description is given in the methodology section, but a short summary is beneficial. He sorts mutual funds into 10 portfolios based on lagged one-year returns from the year 1963 to 1993. These portfolios are held for one year until they are rebalanced.

The results are somewhat mixed. All the portfolios actually exhibit positive monthly excess returns, i.e. after deducting the risk-free rate. However, when the returns are risk-adjusted with the 4-factor model, all alphas become negative. This observation gives evidence of negative abnormal returns in the mutual fund market. Patterns in the results point towards some persistence in the sample. For instance, the excess returns decrease nearly monotonically with the portfolio ranking. The alphas have a similar trend, but it is not that obvious. The top and bottom portfolios are further subdivided into 3 new portfolios for more detailed results. Surprisingly enough, a strategy based on buying the extreme winners and selling the extreme losers yields an excess return of 1,01% per month. The portfolio also earns an alpha value of 0,53% per month with a t-value of 2,72. The paper offers some evidence of performance persistence, but argues that this effect is practically eliminated one year after the portfolio formation period for the previous top performers. The losers however, show persistent underperformance up to year 3 after the formation. Even though the outline gives an impression of a clear pattern, all mean and abnormal returns are not significantly different after one year, which implies that the persistence is brief.

Norwegian equity mutual funds have recently been studied in a similar fashion by Sørensen (2009). The portfolios are again held for one year and the returns are worked through by the Fama and French 3-factor model. The patterns are a little different compared to the study by Carhart. Excess returns are positive for all portfolios, but they seem to be unaffected by portfolio rank. The risk-adjusted alphas actually tend to decrease as the ranking improves, but none of them are significantly different from zero.

2.3 The Efficient Market Hypothesis

This theory has played a central part in modern finance and in the world of asset pricing. A lot started with Fama's Ph.D. thesis (1965) on random walks. In this early work he states some major implications towards the work of "chartists" who actively uses previous returns as a part of their trading strategy, e.g. technical analysis. If asset prices actually follow a random walk, then looking at charts of historical prices adds no real value to an investor. Much of the same goes for fundamental analyses. If the analyst do not have any knowledge that has not already been incorporated in the price, then a fundamental analysis is also worthless in the process of valuing an asset.

In 1969, Fama published a defining paper on market efficiency. This time he puts the whole topic into a framework and introduces three formal levels of efficiency. Each of them is defined by the information subset that is available. The weak form of market efficiency is tested when the information set purely reflects historical data. This means that a valuation process cannot be improved by using previous returns that is considered to be common knowledge. The semi-strong form assumes that all new publically available information is instantly incorporated into asset prices. Testing is therefore primarily based on how prices efficiently adjust to new public information. This can be corporate actions like dividend announcements, stock splits or mergers. The strong form implies that the information set includes all public and private information. This means that no one can use private information in order to trade, and make profits, on a specific asset.

The main part of Fama (1969) is the link between former research and the three forms of market efficiency. During the last remarks of the paper, he concludes that the market is in fact efficient in most ways. The weak and semi-strong form was tested in several ways and they remained intact. Trading algorithms based on past returns were back tested, but no economic profits were registered. Hence, the weak form was not rejected. Event studies were used to test the semi-strong form, and they concluded that approximately all relevant information was incorporated in the price at the time of the events. The strong form did not hold as well as the other two. This is perhaps not that surprising considering its rather extreme position. It was basically two issues that really questioned the reliability of the strong form, that being corporate insiders and specialists on major exchanges. The first one is more or less self-explanatory, while the latter is based on their knowledge of unexecuted orders that can affect the prices dramatically. Nevertheless, the theory of efficient markets was considered to hold quite well.

The aftermath of such strong statements is seldom quiet. This was by no means an exception. It has in fact been under constant attack from both academics and the finance industry ever since its release. However, well-functioning markets are still in general considered to be efficient, at least in the semi-strong form.

How is all this related to persistence in mutual fund returns? In practice, if patterns in returns are persistent over time, then these can be used in order to predict future returns. Investors can furthermore use this to earn better returns on modeled price fluctuations. If this is indeed the case, the weak form of market efficiency will not hold. The forthcoming analysis will focus on how past returns of mutual funds affect future returns. This can in practice give implications towards how consumers can make their investment decisions concerning mutual funds.

3 Methodology

A framework quite similar to the one used by Carhart (1997) is applied in order to look at short-term persistence. The funds are first sorted into four portfolios formed on one-year lagged returns. These portfolios are then rebalanced every one, six and twelve months based on the same criterion. The returns are finally risk-adjusted with the 4-factor model to obtain alphas that might reveal persistence in the sample. Contingency tables based on this sorting are then constructed to expose any patterns in rank dependency.

3.1 Factor Models

All three models are presented, even though the 4-factor model is the only one that is used for analytical purposes. The reason is that they are direct extensions of their smaller predecessor. The CAPM is naturally the foundation of the other models. Jensen (1968) used the CAPM for measuring abnormal performance. Returns that are not explained by the market factor are captured by the intercept, i.e. the alpha in equation (1).

$$R_{i,t} - Rf_t = \alpha_i + \beta_i RMRF_t + \varepsilon_{i,t} \tag{1}$$

The only risk factor, $RMRF_t$, is the return on the market portfolio less the risk-free rate. The dependent variable is asset i's return less the risk-free rate at time t. Excess return, is the common terminology for these variables. Epsilon is the regression's error term.

The Fama and French model includes two new variables, SMB and HML, in their model given by equation (2).

$$R_{i,t} - Rf_t = \alpha_i + \beta_{1,i} RMRF_t + \beta_{2,i} SMB_t + \beta_{3,i} HML_t + \varepsilon_{i,t} \tag{2}$$

The construction of these two variables for the Norwegian market follows the methodology by Fama and French (1996). Stocks are first sorted into two groups, small (S) and big (B), based on their market value relative to the median. They are further sorted by their book-to-market value. Low (L), medium (M) and high (H) are the three new groups. Bernt Arne Ødegaard who delivers the Norwegian factors presents the calculations in his paper from 2011.

$$SMB = average\left({}^{S}/_{L}, {}^{S}/_{M}, {}^{S}/_{H}\right) - average\left({}^{B}/_{L}, {}^{B}/_{M}, {}^{B}/_{H}\right)$$

$$HML = average(S/_H, B/_H) - average(S/_L, B/_L)$$

In general, the SMB factor is a factor-mimicking portfolio that goes long in small-cap stocks and short in large-cap stocks. The HML factor goes long in value stocks and short in growth stocks.

The 4-factor model introduces another variable, PR1YR, that captures the momentum effect. The model is presented in equation (3).

$$R_{i,t} - Rf_t = \alpha_i + \beta_{1,i}RMRF_t + \beta_{2,i}SMB_t + \beta_{3,i}HML_t + \beta_{4,i}PR1YR_t + \varepsilon_{i,t} \qquad (3)$$

The methodology of Carhart (1997) is applied by Ødegaard when he constructs an equivalent factor for the Norwegian market. Stocks are ranked based on past eleven-month returns and placed into three portfolios. The returns of an equally weighted portfolio that consists of the 30% worst performers are then deducted from the returns of the portfolio consisting of the 30% best performers. This means that the factor represents a self-financing portfolio that goes long in past winners and short in past losers.

3.2 Persistence

There are multiple ways to look for persistence in asset prices. The method used in this thesis is originally developed by Hendricks, Patel and Zeckhauser (1993) and later on adopted by Carhart (1997). The basic principle is to sort funds into ranked portfolios based on past returns and then follow up with a performance analysis. A sign of persistence is when the top (bottom) ranked portfolios show superior (inferior) performance relative to the other portfolios.

First of all, an evaluation period must be chosen. Hendricks et al. (1993) investigate several lengths, from one to eight quarters. The strongest results come from a one year period, which later becomes the key part in Carhart's study. Shorter time intervals are more likely to be influenced by autocorrelation which is one of the reasons in favor of an evaluation period equal to one year. This will also be the choice for this analysis.

Next in line is the sorting procedure. The different funds will be put into four ranked portfolios, based on a twelve-month moving average. A fund must have a minimum of twelve months of historical returns to be evaluated. For reasons explained in section 4.2, portfolio formation starts in December 1996. At this point in time, the sample consists of data from 21 mutual funds with sufficient length. The limited number of funds causes restrictions on how many portfolios that can be created. The already mentioned papers used eight and ten main portfolios in their analysis, but they also had a much larger data sample from the U.S. market. The choice therefore falls on four equally weighted portfolios that hopefully give enough detail to look at persistence for this dataset. All of them consist of approximately the same number of funds.

Equally weighted portfolios as opposed to value weighted portfolios are quite common in performance analyses. If a value weighted approach had been used, big funds like pension or corporate funds could have become so influential that they would almost cancel out the effects of smaller and more consumer oriented funds. This analysis wants to look at fund performance, regardless of size. The angle then turns to each fund's ability to create abnormal returns.

After the portfolio formation process is done with, a holding strategy needs to be defined. Carhart (1997) and Sørensen (2009) reform their portfolios after one year. The intention behind this thesis is to take a closer look at shorter time frames. Three different holding strategies are therefore implemented in the following analysis. Each portfolio will be rebalanced after one, six and twelve months in order to reveal any short-term persistence.

3.3 Consistency in Ranking

Another way to look at persistence is how the rankings evolve over the time period. For instance, the top ranked funds in one holding period could keep this ranking in the following periods. This would be sign of consistent ranking, which again leads to persistence in returns. A useful method of illustrating such a property is to create a contingency table. The table will show the historical probability of ending in portfolio j given the initial portfolio i. These calculations will lead to a three-dimensional column chart. The horizontal axes will refer to the initial and the subsequent ranking (i,j), the vertical axis will show the probability of $(j|i)$.

3.4 Validity

In order for ordinary least squares (OLS) to give estimated coefficients with a set of desirable properties, a number of assumptions involving the error term must be satisfied according to Brooks (2008). Note that all the assumptions are made concerning the unobservable disturbance term. Given their theoretical nature, an empirical counterpart must be used to analyze these properties. The regression residuals will play this role.

i. $E(u_t) = 0$
ii. $Var(u_t) = \sigma^2 < \infty$
iii. $Cov(u_t, u_j) = 0$
iv. $Cov(u_t, x_t) = 0$
v. $u_t \sim N(0, \sigma^2)$

The estimators are said to be BLUE (Best Linear Unbiased Estimators) if assumptions i-iv hold. This means that the OLS estimators have the smallest possible variance among linear estimators. The estimated parameters are also considered to be estimators of their true value and form linear combinations of the dependent variable. Finally, they are unbiased, which implies that the average values of the estimators will equal their true theoretical counterparts. The last assumption needs to be fulfilled in order to apply standard inference theory, i.e. use the standard errors that OLS provides directly.

4 Data

This section will focus on the data material used in the statistical analysis. The return data for the mutual funds is provided by Morningstar Norway. All other factors are obtained from publically available sources.

4.1 Selection of Funds

The dataset contains return data for 66 open-ended mutual funds that are alive today. All funds are registered in Norway and invest primarily in Norwegian equity. Index funds have been excluded because of their passive investment strategy. The focus in this thesis is on funds that have a goal of generating abnormal returns for their investors, not those who simply try to track a specific benchmark.

The issue of survivorship bias is highly relevant in this sample. The author was only able to get data from funds that are currently active. It is therefore reasonable to believe that the regression results in section 5 have an upward bias. This will be discussed in more detail later.

4.2 Time Period

The data plots start in the year 1981 when the sample's first fund is initiated. Needless to say, the portfolio sorting procedure will require a certain amount of funds each year. A minimum could be set equal to the number of portfolios, 4, but this may result in very volatile returns. Furthermore, it could in turn give extreme observations that are not representable for the mutual fund market as a whole. This is a consequence of not having data for dead funds. Another argument for starting the time series later is that we want to look at the portfolios as representative averages for the prior top and bottom performers. Therefore one should have multiple funds in each quartile so that potential outliers have less influence on the final results.

The question is then how many funds each portfolio should carry. There is to my knowledge no obvious convention on this matter. The choice fell on an intuitive reasonable limit of 5 funds. This will in practice mean that the 12 month moving averages will begin in December 1996. The end of the sample is restricted by the availability of the explanatory variables used in the 4-factor model. They are provided up to December 2010. This gives the sample a total time series of 169 months, or roughly 14 years.

4.3 Returns

The return data is based on the monthly changes in the fund's net asset value (NAV). The NAV is a fund's total net assets divided by its outstanding shares and it is net of management fees and transaction costs. This is later adjusted for dividend payments on the underlying stocks, assuming that all payments are reinvested.

4.4 Benchmark

The choice of an appropriate benchmark is essential in the multifactor models presented in the previous section. This factor should reflect the fund's investment universe, thus work as a market proxy since the true market portfolio is unobservable.

Every fund is free to choose its own benchmark index. The majority of the sample is currently reporting the Oslo Børs Mutual Fund Index (OSEFX) as their benchmark. The index is constructed to comply with the Undertakings for Collective Investment in Transferable Securities (UCITS) directives which regulate the Norwegian mutual fund industry's portfolio holdings. Because of this, OSEFX will have a maximum weight of 10% for a single security, and securities that exceed 5% of the index value must not combined exceed a total of 40%.[2] The second most used benchmark is the Oslo Børs Benchmark Index (OSEBX). OSEFX is simply a capped version of OSEBX which does not take into consideration the restrictions given by the UCITS directives. The focus in this thesis is on persistence and not individual performance. It is therefore used a common market proxy across the sample. The OSEFX will be this factor since it best reflects the majority of the sample's investment universe. The data is gathered from the Oslo Stock Exchange.

4.5 Risk-Free Rate of Return

The 4-factor model uses the asset's excess return as the dependent variable, and market excess return as one of the risk factors. That is the portfolio return and the market proxy return less a risk-free rate. In practice, there is no asset that yields a return completely without risk. A proxy is therefore needed. Treasury bills are often used for this purpose, Bodie, Kane, & Marcus (2009). The U.S. one-month T-bill is used in Carhart (1997) and Fama and French (1993). The Norwegian interest market is quite different than many others. For instance, Norwegian T-bills are far less liquid than the ones in bigger economies like the U.S. or

[2] http://www.oslobors.no/markedsaktivitet/stockIndexGraph?newt__ticker=OSEFX&newt__menuCtx=1.6.3

Germany. This lack of liquidity can give imprecise observations which might make it unsuitable as a proxy for the risk-free rate. An alternative is the Norwegian Interbank Offered Rate (NIBOR) which reflects the pricing of loans in the interbank market. This is the preferred risk free rate according to Ødegaard (2011).

Due to these reasons, the 1-month NIBOR has been selected as a proxy for the risk-free rate of return. The data is collected from the Norwegian central bank.[3]

4.6 Regression Factors

The market excess return (RMRF) is simply the market portfolio less the risk-free rate. The construction of the remaining factors, HML, SMB and PR1YR, is described thoroughly in section 3.1. These are obtained from the web page of Bernt Arne Ødegaard who has constructed them for the Norwegian market.[4] The data is only available up to December 2010, which will mark the end of the sample period. This is unfortunate because the return data stretches all the way through 2011, so one year of fund returns are therefore lost.

4.7 Survivorship and Incubation Bias

The sample only consists of mutual funds that are alive today. The funds that have ceased to exist during the time span must have done so for a reason. It seems reasonable that mutual funds with bad historic returns find it more difficult to attract capital and to stay alive. This might give an upward bias in the sample returns.

There has been a large debate concerning the importance of survivorship bias. Wermers (1997) explain how other studies have found survivorship bias to be a small problem. One of the key features is that they did not find a significant difference in the returns of surviving funds relative to the whole universe of funds. Malikel (1995) points out that exclusion of non-surviving funds significantly biases the performance results. The Norwegian fund market is evaluated in Sørensen (2009). He reports a statistically significant difference of -0,31% per month for dead versus alive funds in the time period 1996:01 – 2008:12. This is quite similar to the time period used in this thesis, so a certain amount of survivorship bias must be expected from the data sample.

[3]http://www.norges-bank.no/no/prisstabilitet/rentestatistikk/nibor-effektiv-rente-manedsgjennomsnitt-av-daglige-data/

[4]http://finance.bi.no/~bernt/financial_data/ose_asset_pricing_data/index.html

The U.S. mutual fund industry has also been accused of using an incubator strategy where fund suppliers privately start up several funds closed off to the public. After an evaluation period, they pick the best funds to go public. This effect is studied by Evans (2009) who finds evidence of higher risk-adjusted returns for funds in incubation than non-incubated funds. This could also bias the returns in this sample. However, the Norwegian fund market is relatively small and transparent compared to the U.S. market. Very little attention has been given to this subject domestically, so it is assumed that a potential effect like this is negligible.

4.8 Descriptive Statistics

This part will in general present historical features of the key variables described in the previous sections along with the ranked portfolios.

4.8.1 Overall Returns

The overall monthly returns are calculated as an arithmetic mean of an equally weighted portfolio consisting of all the funds in the sample stretching from January 1997 to December 2010. The start date is the first month a portfolio is constructed based on the 12-month moving average described in section 4.2.

Table 1: Fund and benchmark statistics

Portfolio	Mean	Std Dev	Max	Min	Skewness	Kurtosis
All funds (EW)	1,04 %	6,98 %	15,58 %	-25,52 %	-0,87	1,64
OSEFX	1,00 %	7,30 %	16,52 %	-27,17 %	-1,11	2,62

All statistics in percentages are presented in monthly returns. The moments are based on monthly gross returns in the time period 1997:01 – 2010:12.

As we can see from Table 1, the funds have a higher average return and a lower standard deviation than the benchmark index. So in terms of gross returns, the fund sample seems to have performed slightly better than the fund index.

4.8.2 Ranked Portfolios

A detailed walkthrough of Table 2 would simply be of little value to the remaining text and is therefore skipped. However, a few points are still worth mentioning. One can observe from the third moment that all ranked portfolios are slightly skewed to left, which can be due to relatively low minimum values compared to the maximum values. The monthly means are still positive and circles around 1%. This is not the case for the spread portfolios. An interesting observation concerning the spreads is that they are all positive, but they decline substantially when the holding period increase. The means start off rather impressing with the one-month strategy, but become dangerously close to zero when the holding period is set to twelve months. All of the main distributions are presented in the appendix for further detail.

Table 2: Ranked portfolio statistics

Portfolio	Mean	Std Dev	Max	Min	Skewness	Kurtosis
one-month:						
1 (high)	1,26 %	7,31 %	23,27 %	-26,14 %	-0,63	1,60
2	1,07 %	6,97 %	15,34 %	-25,28 %	-0,92	1,67
3	0,98 %	7,02 %	15,50 %	-25,16 %	-0,86	1,52
4 (low)	0,81 %	7,01 %	16,36 %	-25,51 %	-0,89	1,75
1-4 spread	0,45 %	2,16 %	13,59 %	-5,01 %	2,06	10,26
six-month:						
1 (high)	1,11 %	7,23 %	16,23 %	-26,08 %	-0,79	1,35
2	1,08 %	7,01 %	15,65 %	-25,42 %	-0,91	1,58
3	0,99 %	7,06 %	16,67 %	-25,09 %	-0,90	1,76
4 (low)	0,94 %	7,00 %	20,85 %	-25,51 %	-0,72	1,73
1-4 spread	0,16 %	2,13 %	13,23 %	-6,50 %	1,36	9,68
twelve-month:						
1 (high)	1,05 %	7,22 %	16,23 %	-25,59 %	-0,77	1,32
2	1,00 %	7,06 %	15,65 %	-24,84 %	-0,96	1,75
3	1,03 %	7,12 %	16,67 %	-26,54 %	-0,88	1,79
4 (low)	1,02 %	6,90 %	19,28 %	-25,01 %	-0,73	1,55
1-4 spread	0,03 %	2,07 %	13,23 %	-5,56 %	1,86	11,32

All statistics in percentages are presented in monthly returns. The moments are based on monthly gross returns in the time period 1997:01 – 2010:12. The table is divided into three parts, one for each holding strategy.

These properties are better shown in the figures below where cumulative returns on all the portfolios are plotted against the sample time series. The spreads are clearly getting thinner as the post-formation period increases, and it seems like returns are closing in on the fund index.

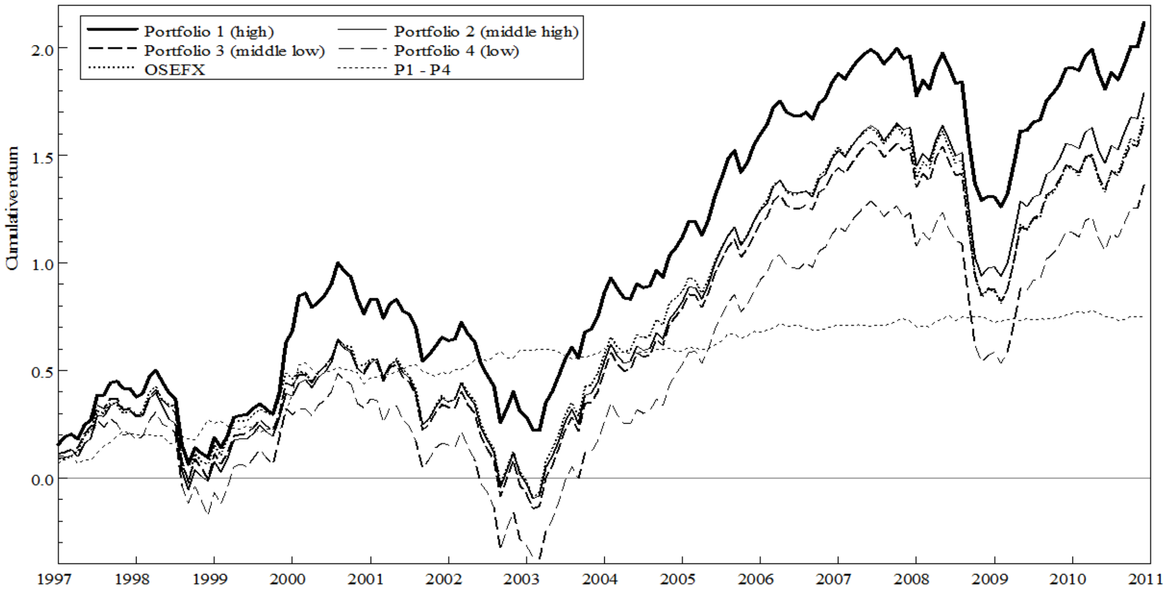

Figure 2: Cumulative gross returns on ranked portfolios with a one-month holding strategy

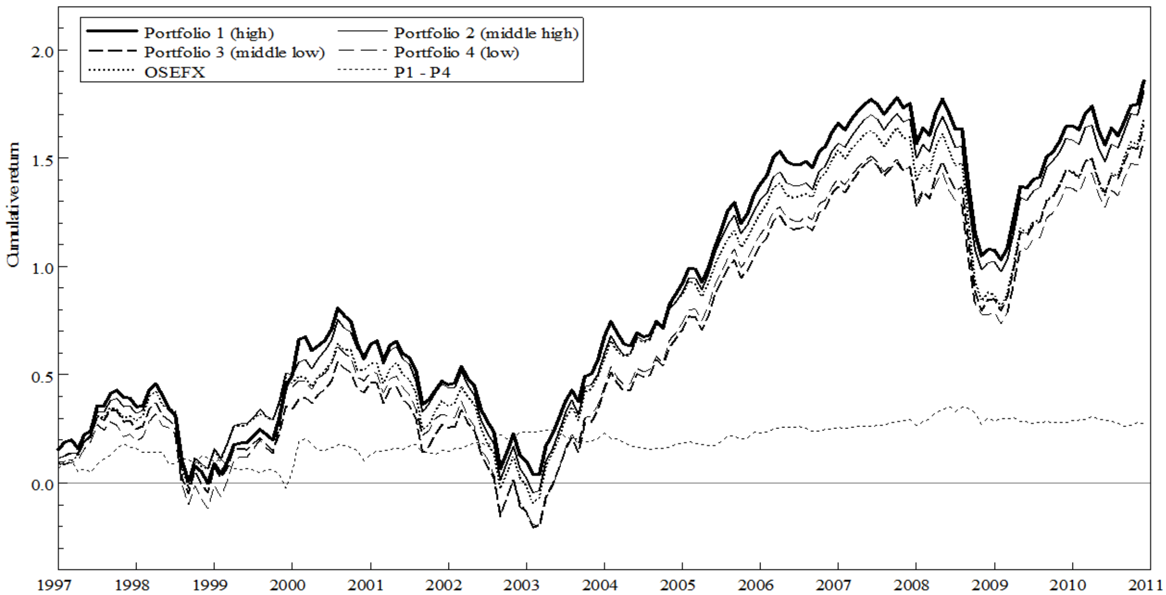

Figure 3: Cumulative gross returns on ranked portfolios with a six-month holding strategy

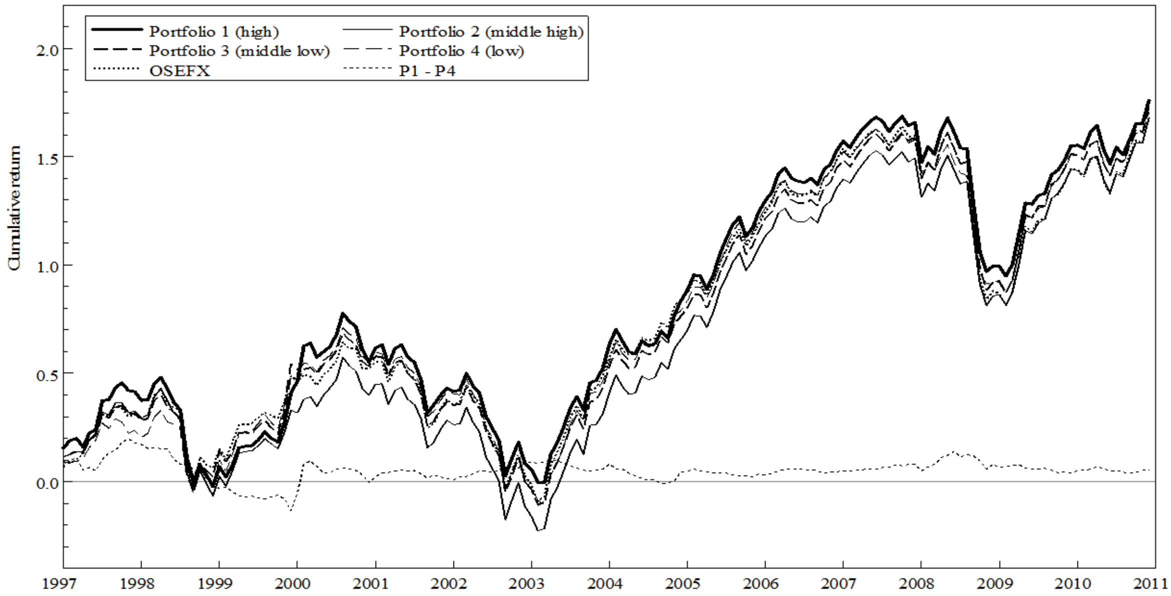

Figure 4: Cumulative gross returns on ranked portfolios with a twelve-month holding strategy

4.8.3 Regression Factors

The past movements of the factors could give indications about their importance in the final 4-factor model. Sørensen (2009) argues that the movement from the CAPM to the F&F 3-factor model generates major improvements in the explanation of the cross-sectional variation, the momentum factor (PR1YR) should however be dropped in the analysis. It yields a relatively high return, but it is statistically insignificant in his regressions. This thesis is based on a different sample of fund returns and has a shorter time frame, so a separate evaluation of the fourth factor is needed.

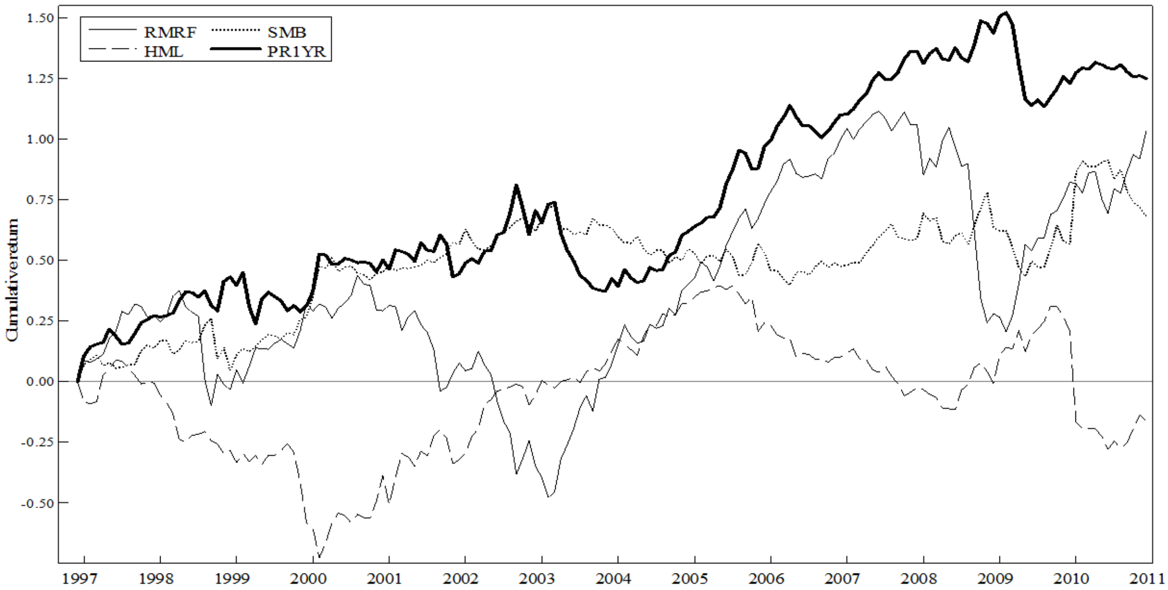

Figure 5: Cumulative gross returns on regression factors

We can see the portfolio that represents a momentum strategy (PR1YR) has the highest cumulative return in most years. The difference relative to the other factors also seems to increase dramatically during the last four years of the sample. Perhaps the most upsetting feature of the graph is the low returns on the HML factor. This is quite different from what is presented in Sørensen (2009) where the time period starts in 1982. The SMB yields a fairly stable and positive cumulative return.

Table 3: Statistics on regression factors

					Cross-correlation			
Factor portfolio	Mean	Std Dev	Max	Min	RMRF	SMB	HML	PR1YR
RMRF	0,61 %	7,35 %	16,35 %	-27,73 %	1,00			
SMB	0,41 %	4,93 %	29,82 %	-16,74 %	-0,46	1,00		
HML	-0,10 %	5,63 %	11,62 %	-37,75 %	-0,19	-0,37	1,00	
PR1YR	0,74 %	5,07 %	15,43 %	-16,75 %	-0,25	0,20	0,02	1,00

All numbers are based on monthly returns in the time period 1997:01 – 2010:12.

Every portfolio, except HML, exhibit positive average returns. The PR1YR statistics confirm what is observed in Figure 5. It has the highest mean and a rather small standard deviation. This implies that a trading strategy based on the construction of PR1YR could have been successful during the time span in terms of gross returns. The fact that it is so influential gives reason to use the 4-factor model instead of the 3-factor model. This factor will later show significant results in the regression analysis as well.

As one can see from the cross-correlation table, multicollinearity looks to be of no serious concern. Interestingly enough, market excess returns (RMRF) are negatively correlated with all the other factors. The CAPM alone will therefore miss out on quite a bit of variation.

5 Results

Three different trading strategies have been run in order to look at persistence in the sample. Linear regression validity marks the starting point of this section, while aggregated numbers from all of the funds are next in line. The results from the sorted portfolios will then be introduced in ascending order, based on the strategy's holding period. All tables will report results from the CAPM and the 4-factor model. The latter model is preferred in the risk-adjustment process, while the CAPM is included for comparative reasons only. Contingency tables are presented at the end to see how rankings have evolved throughout the sample period.

5.1 Diagnostic Tests

As mentioned in the methodology section, all five assumptions, i-v, must hold in order to get valid inferences in the regressions. However, the normality assumption does not need to be satisfied for OLS to give best linear unbiased estimators (BLUE). Each of the assumptions will further be explained and evaluated up against the applied data sample.

i. The assumption of an expected value of the error term equal to zero will actually never be violated as long as an intercept term is included in the regression. As long as the underlying theory does not demand a regression through the origin, this assumption is of no concern. The main model used in this analysis is the 4-factor model which includes an intercept, thus the assumption holds.
ii. Homoscedasticity implies that the variance of the errors is constant. If the assumption does not hold, we say that the errors are heteroscedastic. This gives rise to some practical implications. First, the quality of the model predictions will systematically depend upon the values of the explanatory variables. Second, the OLS estimators are no longer BLUE. The method used to detect potential heteroscedasticity for this sample is the White test with squared values. It is conducted by running an auxiliary regression with the squared residuals as the dependent variable on the ordinary explanatory variables and their squared values as well. One can in addition use cross products of the right hand side variables, but this reduces the degrees of freedom substantially in this case. The cross products are therefore left out in the regression. A standard F-test is then used on the estimators to test the joint hypothesis of no dependency. The results presented in Table 4 indicate a relatively strong presence of

heteroscedasticity in all regressions except one. This makes the following t-statistics questionable, so tables with robust standard errors are presented in the appendix. These follow the method of Newey and West (1987) that corrects for heteroscedasticity.

iii. Number three implies that the errors should not be serially correlated, i.e. uncorrelated with each other at different points in time. A violation of this assumption will as mentioned earlier lead to OLS not giving estimates that are BLUE. In order to identify any serial correlation, a portmanteau test is applied. This is equivalent to the Ljung-Box test that checks whether or not the autocorrelation coefficients are jointly equal to zero. The test results say that all three top portfolio regressions show signs of serial correlation. The Newey and West (1987) procedure will also give standard errors that are corrected for serial correlation.

iv. This assumption states that the errors must be unrelated to the explanatory variables. An alternative formulation is that the variables must be non-stochastic and they need to be exogenous. An assumption like this is harder to test explicitly, so a formal procedure will not be undertaken to investigate it. In practice, the 4-factor model with its underlying theory is trusted in the context of satisfying these properties.

v. The last one demands that the errors are normally distributed. This means that the errors should have a mean equal to zero and a constant variance, which are already assumed. They also need to be symmetric about its mean, i.e. a skewness of zero. The assumption also implies that the kurtosis should equal to 3. If we take a look at the descriptive statistics of the regressions, we can see that every ranked portfolio has a negative skewness and a kurtosis well below the required level. A Doornik-Hansen normality test is applied to formally investigate this matter. From the test statistics below, we can see that most regressions reject the null hypothesis of normality. This gives reason to question the validity of the standard t-tests that will be conducted later in the results section. There is unfortunately no obvious procedure to account for this weakness in the model. However, one can take comfort in the central limit theorem that implies that the test statistics will asymptotically have the desired distribution for large samples. It is therefore assumed that this sample is large enough, so that the inferences can be trusted.

From the diagnostics presented above, some actions have been made to ensure the validity of the regressions. Tables in the appendix are therefore presented with underlying standard errors that are corrected for heteroscedasticity and serial correlation when it is required. The main difference between the tables of ordinary standard errors and corrected standard errors is that the t-statistics unsurprisingly show lower absolute values in the latter case. This goes primarily for the explanatory variables, while the intercept occasionally becomes more significant. The consequences of this will not in any way affect the conclusions being made, and that is why the tables with corrected values are presented in the appendix.

Table 4: Test statistics for model validity

Portfolio	H_0: No heteroskedasticity	H_0: No serial correlation	H_0: Normally distributed residuals
one-month:			
1 (high)	[0.0000]**	[0.0031]**	[0.0000]**
2	[0.0540]	[0.8795]	[0.0000]**
3	[0.0000]**	[0.2392]	[0.0003]**
4 (low)	[0.0001]**	[0.2631]	[0.1907]
six-month:			
1 (high)	[0.0000]**	[0.0112]*	[0.0000]**
2	[0.0003]**	[0.9237]	[0.0710]
3	[0.0195]*	[0.4160]	[0.6038]
4 (low)	[0.0000]**	[0.3135]	[0.0000]**
twelve-month:			
1 (high)	[0.0000]**	[0.0120]*	[0.0000]**
2	[0.0004]**	[0.7502]	[0.0277]*
3	[0.0000]**	[0.5681]	[0.0065]**
4 (low)	[0.0000]**	[0.4494]	[0.0000]**

Tests for heteroscedasticity, serial correlation and normality are conducted for each holding period. The numbers are p-values where the asterisks imply:

*significant at the 5% level

**significant at the 1% level

5.2 All Funds

An equally weighted portfolio is created of all the funds in the sample. The statistics here are not relevant to the main task, but it serves as a useful summary that can be compared to the final results. Table 5 shows that the mutual funds create a positive excess return of 0,66% per month over the sample period. This is equivalent to an annualized excess return of 8,15%. The market benchmark yields a 7,62% annualized excess return when the risk-free rate is deducted. It can further be observed that the sample of funds has created higher and less volatile returns compared to the OSEFX.

The risk-adjusted excess return is highly insignificant. This goes for both the CAPM and the Carhart 4-factor model. The funds are therefore unable to create abnormal risk-adjusted returns as a unit. The factor loadings reveal a market beta close to one, and positive significant exposure towards small-cap stocks. A somewhat surprising result is the negligible increase in the adjusted R^2 when including the additional three factors. In the 4-factor model's defense, increasing the explained cross-sectional variation from 97% is not an easy task.

Table 5: EW portfolio of all funds

			CAPM			4-factor model					
	Excess return	Std Dev	Alpha	RMRF	Adj R^2	Alpha	RMRF	SMB	HML	PR1YR	Adj R^2
All funds EW	0,66 %	7,04 %	0,08 %	0,94	0,97	-0,01 %	0,98	0,10	0,00	0,02	0,97
			(0,81)	(-4,45)		(-0,08)	(-1,44)	(4,48)	(-0,26)	(1,38)	

All numbers are based on monthly returns in the time period 1997:01 – 2010:12. The mutual funds are sorted into an equally weighted portfolio, where the monthly excess returns are regressed against the CAPM and the 4-factor model. The t-statistics are in parenthesis below their respective coefficients. The null hypothesis for the RMRF factors is: $\beta=1$.

5.3 One-Month Holding Strategy

The funds are now sorted into four equally weighted portfolios based on their lagged one-year returns. The top 25% funds form portfolio 1, while the bottom 25% form portfolio 4. Table 6 shows increasing excess returns with ranking. The previous top funds seem to outperform the others based on simple returns. The top ranked portfolio yields a steady 11,02% annualized excess return, which is substantially more than the sample average in Table 5.

The risk-adjusted alphas give a similar picture of increasing returns with ranking. The results are however insignificant for all portfolios, even at the 10% level. This means that none of the portfolios have been able to earn significant abnormal returns in the sample period.

As to model specification, both of them show very high explanatory power with adjusted R-squares above 0,9 for all portfolios. The 4-factor model is unable to extensively increase the explained variation compared to the CAPM, but it shows significant exposure to the SMB and the PR1YR factor in several cases. Only the top ranked portfolio has significant exposure to the HML factor, but this is only at the 10% level. The market betas are equal to one, except for portfolio 2 that has a beta slightly below one. An interesting observation is the increasing exposure, based on ranking, towards the one-year momentum effect. Better ranked portfolios seem to have higher factor loadings on the PR1YR factor. This is also the case in Carhart (1997) and Wermers (1997) in their study of the U.S. market. A discussion on this topic is outside the scope of this thesis, but it shows possible patterns in the styles of the grouped equity funds.

A theoretical self-financing portfolio that goes long in the previous top performers and short in the previous bottom performers is constructed to look at the possible return of such a strategy. Monthly excess returns are on average 0,45%, while the alpha is 0,28% per month and significant at the 10% level. Such a strategy is practically impossible to implement in the Norwegian market, but it gives indications of rank dependency on ex post returns. Although the risk-adjusted abnormal return is not significant at the conventional 5% level, it still questions the efficiency of the fund market.

Table 6: Portfolios ranked on lagged one-year returns and reformed every month

			CAPM			4-factor model					
Portfolio	Excess return	Std Dev	Alpha	RMRF	Adj R^2	Alpha	RMRF	SMB	HML	PR1YR	Adj R^2
1 (high)	0,88 %	7,36 %	0,29 %	0,95	0,91	0,10 %	1,01	0,14	-0,06	0,13	0,93
			(1,68)	(-1,94)		(0,62)	(0,45)	(3,50)	(-1,75)	(4,04)	
2	0,68 %	7,03 %	0,10 %	0,94	0,97	0,04 %	0,97	0,06	0,00	0,03	0,97
			(1,12)	(-4,64)		(0,43)	(-2,19)	(2,63)	(-0,06)	(1,64)	
3	0,60 %	7,07 %	0,02 %	0,95	0,98	-0,05 %	0,98	0,09	0,01	0,01	0,98
			(0,19)	(-4,25)		(-0,62)	(-1,20)	(4,24)	(0,73)	(0,88)	
4 (low)	0,43 %	7,07 %	-0,15 %	0,94	0,95	-0,18 %	0,98	0,15	0,03	-0,06	0,96
			(-1,18)	(-3,76)		(-1,54)	(-1,24)	(4,82)	(1,14)	(-2,70)	
1-4 spread	0,45 %	2,16 %	0,44 %	0,02	0,00	0,28 %	0,04	-0,01	-0,08	0,19	0,22
			(2,61)	(0,81)		(1,84)	(1,44)	(-0,18)	(-2,69)	(6,26)	

All numbers are based on monthly returns in the time period 1997:01 – 2010:12. The mutual funds are sorted into equally weighted portfolios based on their past twelve-month return. Funds with the highest past returns are put into portfolio 1, while portfolio 4 consists of funds with the lowest returns. Monthly excess returns are regressed against the CAPM and the 4-factor model. RMRF is the excess return on the market proxy. SMB and HML are factor-mimicking portfolios for the size and value effect. PR1YR is a factor-mimicking portfolio for the one-year momentum effect. The t-statistics are in parenthesis below their respective coefficients. All portfolios, except the 1-4 spread portfolio, have the null hypothesis of a RMRF coefficient equal to one, β_1=1.

Figure 6 show the patterns described earlier. One can clearly see that both excess returns and risk-adjusted alphas decline with portfolio ranking. The columns should have been equal from a market efficiency point of view. The trend on these two indicators shows something quite different. Nonetheless, it is important to remember that no alpha is significantly different from zero.

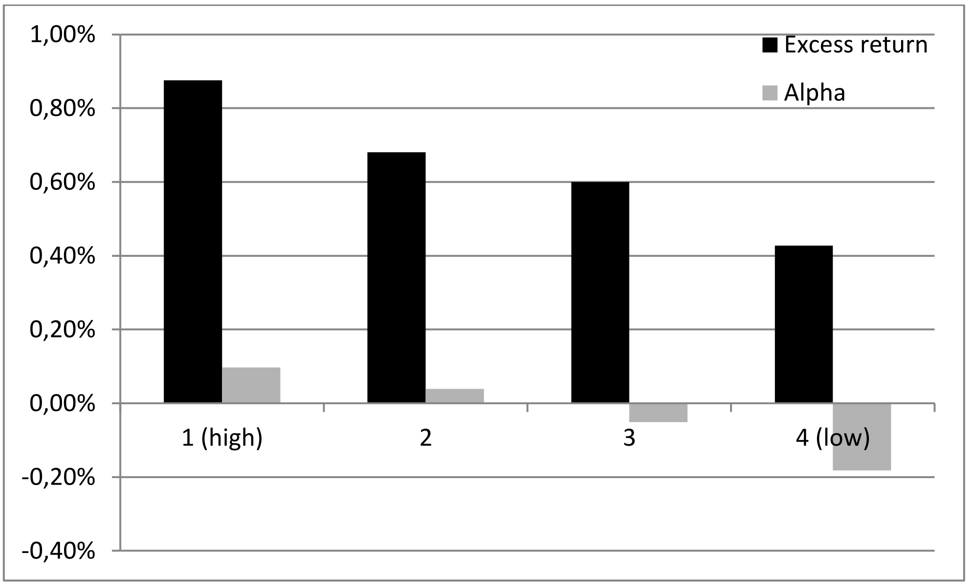

Figure 6: Monthly excess return and alpha for portfolios ranked on lagged one-year returns and rebalanced every month

5.4 Six-Month Holding Strategy

The portfolio sorting procedure is the same as before, the only difference is the holding period which is now set to six months. Excess returns are positive and increasing with portfolio ranking. The pattern is basically the same as in the one-month holding strategy, but the declining trend is less steep. Annualized numbers are still quite high, as the top ranked portfolio yields a 9,01% excess return.

When it comes to risk-adjusted alphas, the picture is a little different. The top ranked portfolio has a smaller alpha than the two next portfolios, as well as being negative. The subsequent portfolios show a declining pattern, but all alphas are still insignificant. Hence, no portfolios are able to earn significant abnormal returns with the longer six-month holding strategy.

The explanation of cross-sectional returns is again roughly the same for the two models. Market betas are all approximately equal to one, while none of the portfolios show significant exposure to the HML factor. The size factor shows something rather different. All coefficients are positive and significant at the 5% level. The two top portfolios also show significant exposure to the PR1YR factor and it seem to increase with portfolio ranking, as it did under the one-month holding period.

The self-financing portfolio is less noticeable than before. It still produces a positive average excess return, but the alpha is highly insignificant with a t-value of only 0,06. So in general, this holding strategy has produced inferior results compared to the one-month holding strategy.

Table 7: Portfolios ranked on lagged one-year returns and reformed every six months

			CAPM			4-factor model					
Portfolio	Excess return	Std Dev	Alpha	RMRF	Adj R^2	Alpha	RMRF	SMB	HML	PR1YR	Adj R^2
1 (high)	0,72 %	7,28 %	0,14 %	0,95	0,92	-0,05 %	1,01	0,16	-0,02	0,11	0,93
			(0,85)	(-2,32)		(-0,37)	(0,59)	(4,21)	(-0,80)	(3,81)	
2	0,69 %	7,07 %	0,11 %	0,95	0,97	0,04 %	0,97	0,07	-0,01	0,03	0,98
			(1,26)	(-4,24)		(0,51)	(-1,82)	(2,92)	(-0,52)	(1,91)	
3	0,60 %	7,12 %	0,01 %	0,96	0,98	-0,02 %	0,98	0,07	0,00	0,00	0,98
			(0,16)	(-3,75)		(-0,29)	(-1,57)	(3,15)	(0,12)	(-0,25)	
4 (low)	0,56 %	7,06 %	-0,01 %	0,93	0,94	-0,06 %	0,97	0,14	0,01	-0,04	0,95
			(-0,11)	(-3,78)		(-0,50)	(-1,42)	(4,11)	(0,40)	(-1,51)	
1-4 spread	0,16 %	2,13 %	0,15 %	0,02	0,00	0,01 %	0,05	0,02	-0,04	0,15	0,13
			(0,93)	(0,76)		(0,06)	(1,72)	(0,58)	(-1,07)	(4,82)	

All numbers are based on monthly returns in the time period 1997:01 – 2010:12. The mutual funds are sorted into equally weighted portfolios based on their past twelve-month return. Funds with the highest past returns are put into portfolio 1, while portfolio 4 consists of funds with the lowest returns. Monthly excess returns are regressed against the CAPM and the 4-factor model. RMRF is the excess return on the market proxy. SMB and HML are factor-mimicking portfolios for the size and value effect. PR1YR is a factor-mimicking portfolio for the one-year momentum effect. The t-statistics are in parenthesis below their respective coefficients. All portfolios, except the 1-4 spread portfolio, have the null hypothesis of a RMRF coefficient equal to one, β_1=1.

The columns in Figure 7 show steadier returns than the previous one. Excess returns are increasing with portfolio ranking, but at a lower rate than before. This is the main reason why the spread portfolio has performed much worse with this strategy. Also the alphas are closer to zero for the top and bottom portfolio.

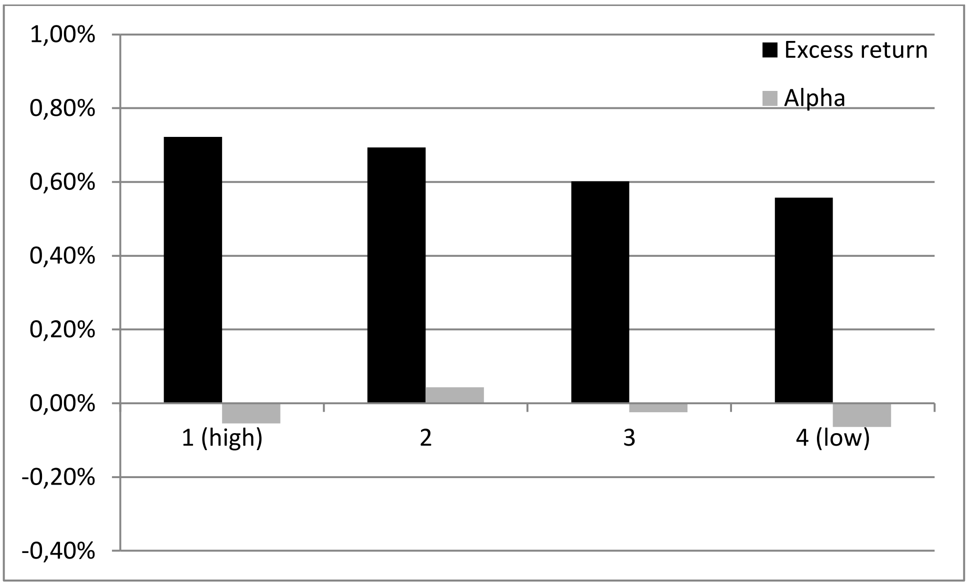

Figure 7: Monthly excess return and alpha for portfolios ranked on lagged one-year returns and rebalanced every six months

5.5 Twelve-Month Holding Strategy

This holding period is the same as the one used in Carhart (1997) and Sørensen (2009). The patterns that emerged in the two previous strategies are now basically gone. Excess returns are still positive but no obvious trend can be spotted. The highest simple return belongs to the top ranked portfolio once again, and it yields an 8,26% annualized return.

Risk-adjusted alphas actually show an opposite trend compared to the one-month holding strategy. The alphas decrease with portfolio ranking, so the top ranked portfolio exhibit the lowest risk-adjusted return. All of them have t-values well below the conventional limits.

The 4-factor model is also in this setting unable to improve the high adjusted R^2 substantially from the CAPM. The market beta is significantly below one only for the bottom portfolio. HML and SMB coefficients show similar behavior as before. Exposure to the PR1YR factor has changed some from the former strategies. It is no longer increasing with portfolio rank and only the top portfolio has a significant coefficient at the 5% level.

Results concerning the self-financing portfolio are not very surprising. The spread between portfolio one and four is at its lowest compared to the other strategies. A mere 0,03% monthly excess return is produced and the alpha is highly insignificant.

Table 8: Portfolios ranked on lagged one-year returns and reformed every twelve months

			CAPM			4-factor model					
Portfolio	Excess return	Std Dev	Alpha	RMRF	Adj R^2	Alpha	RMRF	SMB	HML	PR1YR	Adj R^2
1 (high)	0,66 %	7,28 %	0,08 %	0,95	0,92	-0,11 %	1,02	0,18	-0,01	0,10	0,93
			(0,50)	(-2,34)		(-0,75)	(0,77)	(4,64)	(-0,37)	(3,34)	
2	0,62 %	7,11 %	0,03 %	0,95	0,97	-0,03 %	0,99	0,09	0,02	0,00	0,97
			(0,32)	(-3,62)		(-0,32)	(-0,90)	(3,85)	(0,97)	(0,26)	
3	0,65 %	7,17 %	0,05 %	0,96	0,97	0,00 %	0,98	0,06	-0,02	0,02	0,98
			(0,62)	(-3,06)		(-0,01)	(-1,23)	(2,61)	(-1,28)	(1,37)	
4 (low)	0,63 %	6,95 %	0,06 %	0,92	0,95	0,02 %	0,95	0,10	0,00	-0,02	0,96
			(0,55)	(-4,79)		(0,19)	(-2,52)	(3,31)	(0,02)	(-0,94)	
1-4 spread	0,03 %	2,07 %	0,02 %	0,02	0,00	-0,13 %	0,07	0,08	-0,01	0,12	0,11
			(0,10)	(1,14)		(-0,86)	(2,63)	(1,95)	(-0,36)	(3,91)	

All numbers are based on monthly returns in the time period 1997:01 – 2010:12. The mutual funds are sorted into equally weighted portfolios based on their past twelve-month return. Funds with the highest past returns are put into portfolio 1, while portfolio 4 consists of funds with the lowest returns. Monthly excess returns are regressed against the CAPM and the 4-factor model. RMRF is the excess return on the market proxy. SMB and HML are factor-mimicking portfolios for the size and value effect. PR1YR is a factor-mimicking portfolio for the one-year momentum effect. The t-statistics are in parenthesis below their respective coefficients. All portfolios, except the 1-4 spread portfolio, have the null hypothesis of a RMRF coefficient equal to one, β_1=1.

The distribution of excess returns appears somewhat arbitrary in this setting. Every one of them show rather similar excess returns and the ranking do not seem to affect the results. The reversed trend compared to the one-month alphas can be observed in Figure 8.

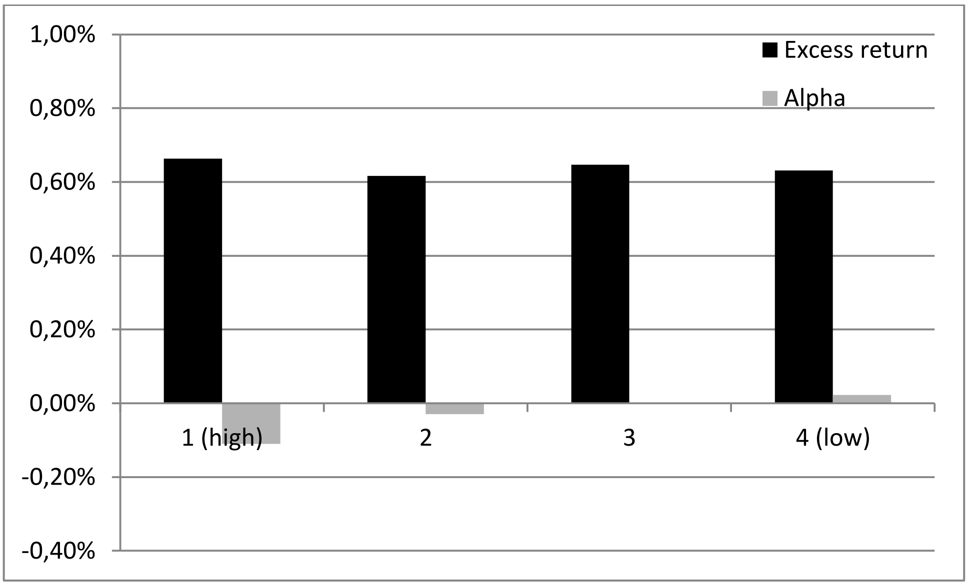

Figure 8: Monthly excess return and alpha for portfolios ranked on lagged one-year returns and rebalanced every twelve months

5.6 Trend Summary

Figure 9 is basically a mirror image of the previous three charts. The lines at the top represent excess returns while the corresponding bottom ones are the risk-adjusted returns. The first thing that comes to mind is the declining spread of excess returns between the top and bottom portfolio as the holding period increases. This may be observed from the slopes in the chart below. Excess returns for the one-month holding period has a steep negative slope compared to the six-month line. This trend disappears somewhere between six and twelve months as the remaining line show no sign of dependent behavior towards the portfolios. If it is looked past the fact that alphas are not significantly different from zero, they do show some interesting features. The slope of the one-month line is again negative and steeper than the other two. The real surprise is the twelve-month line that shows a steady increase as the portfolio ranking gets worse. This could of course be a result of mere chance due to the insignificant alpha values.

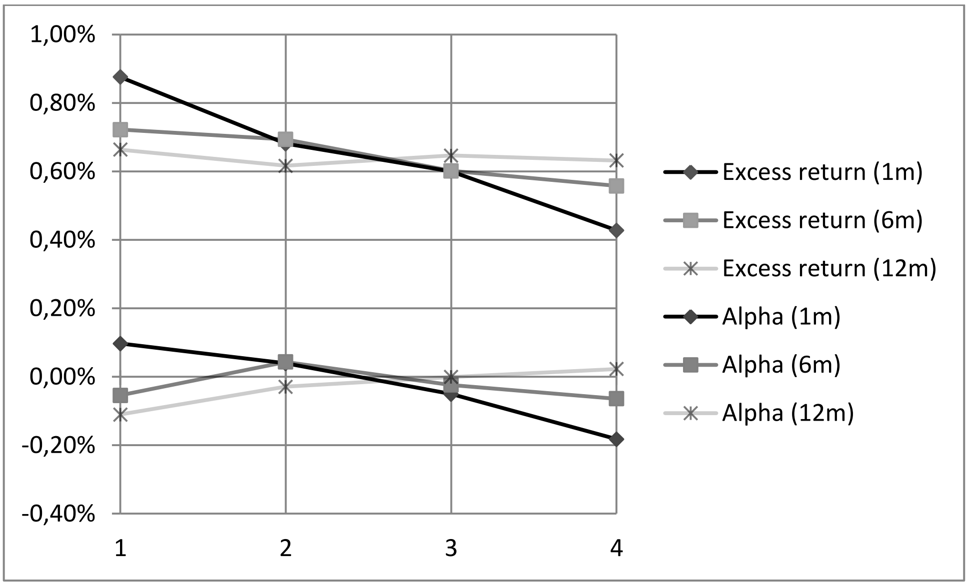

Figure 9: Summary of monthly excess return and alpha for portfolios ranked on lagged one-year returns

5.7 Consistency in Ranking

Contingency tables are constructed for each of the holding strategies throughout the sample period. The three forthcoming figures illustrate these tables. The columns reflect the historical probability of being in portfolio *j* in one period, given the initial portfolio ranking *i*.

Four dominating columns can be seen in the one-month holding strategy. The pairs (1,1), (2,2), (3,3) and (4,4) all have probabilities above 60%. In general, the event of a portfolio getting the same ranking two months in a row is quite likely. The table also indicates that if a portfolio is top ranked in one period, it is an 81% chance of it maintaining this ranking the next period. If a portfolio is bottom ranked in one period, it is a 79% chance of it keeping this ranking the next period. Needless to say, the other probabilities are fairly low.

$$\text{One-month holding strategy} \begin{cases} Probability\,[1|1] = 81\% \\ Probability\,[4|4] = 79\% \end{cases}$$

A six-month holding strategy gives a more even distribution. The highest columns are the same as before, but they are much less influential. The probabilities are almost monotonically changing where the initial ranking is either 1 or 4. The distributions for the other two initial rankings seem more arbitrary. The probabilities of persistent over or under performers are much lower with this longer holding period, they are however above 50% which is still relatively high.

Six-month holding strategy $\begin{cases} Probability\ [1|1] = 54\% \\ Probability\ [4|4] = 51\% \end{cases}$

Turning to the more conventional twelve-month holding period, the distribution has evened out substantially and no pattern really points out. The highest column is again at the (1,1) path, but it is coming close to 25% which would have indicated no persistence in ranking. This is immediately the case for (4,4) column.

Twelve-month holding strategy $\begin{cases} Probability\ [1|1] = 32\% \\ Probability\ [4|4] = 24\% \end{cases}$

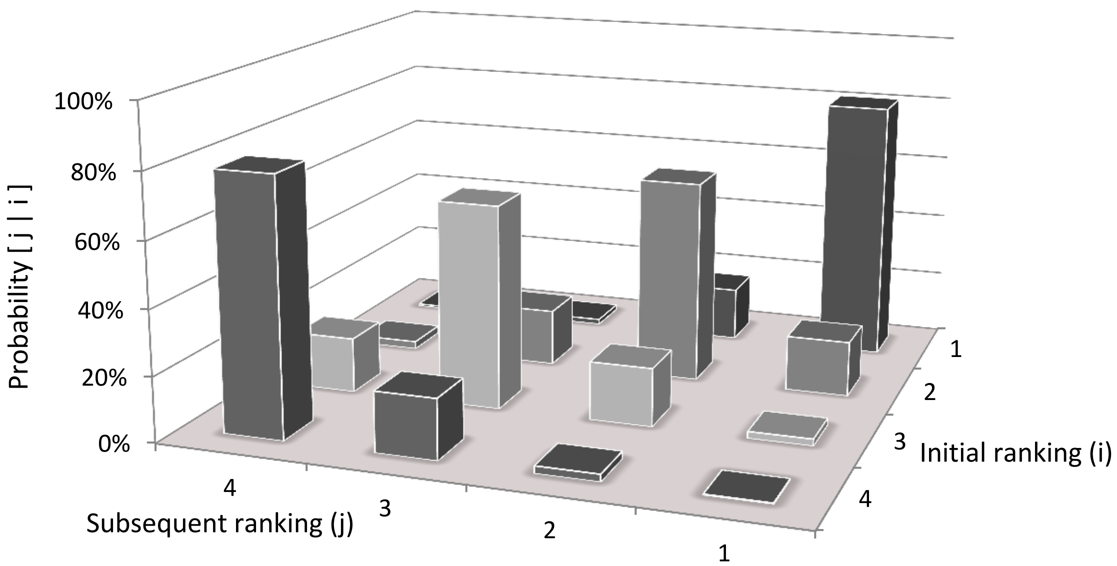

Figure 10: Contingency table of the one-month holding strategy

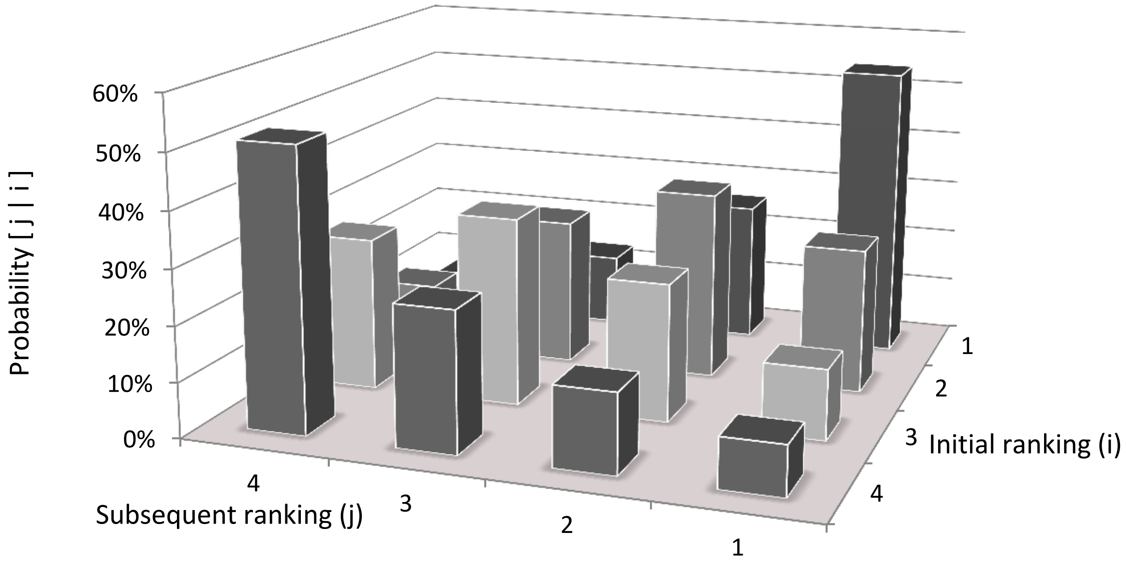

Figure 11: Contingency table of the six-month holding strategy

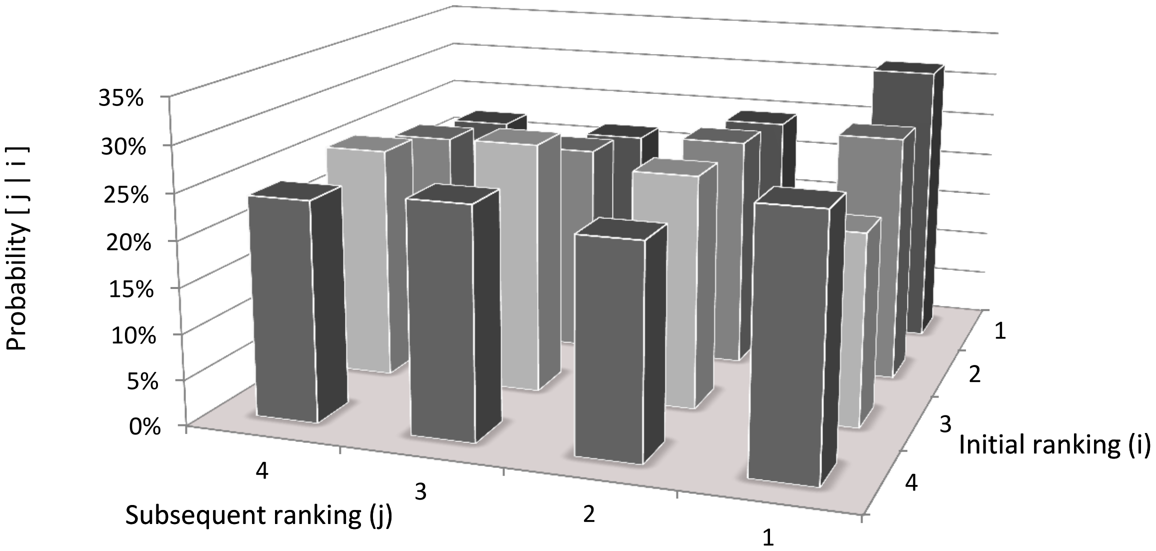

Figure 12: Contingency table of the twelve-month holding strategy

6 Conclusion

Two methods have been used to analyze the short-term persistence in the sample consisting of Norwegian equity mutual funds. The first one ranks portfolios based on past returns, which are later regressed against the 4-factor model. The second method is more graphical. Rank consistency is presented in a column chart with historical probabilities on the vertical axis. Both of these methods are applied for three different holding periods; one, six and twelve months.

The sample of funds has outperformed the mutual fund benchmark in terms of gross returns. The difference is no more than 40 basis points per month, so the potential survivorship bias could be a considerable source to this spread. This equally weighted portfolio of all funds in the sample show a positive annualized excess return of 8,15% over the sample period. In addition, the fund returns have been less volatile than the OSEFX. Hence, the funds have performed slightly better than the market benchmark on these two basic indicators.

Different holding strategies have certainly created mixed results. The ranked portfolio excess returns seem to be more arbitrary distributed when the holding period increases. For the one-month rebalancing procedure, a clear trend is observed. It tells us that funds with high past returns have higher excess returns the next month relative to the others. A similar structure holds when the portfolios are rebalanced every six months, but the impact from the ranking is less obvious. This trend disappears completely when the portfolios are rebalanced every twelve months, as it creates more or less even excess returns across the ranked portfolios. The self-financing portfolio that goes long in past winners and short in past losers reflects this matter with a declining average return when the holding period increases. It is very close to zero for the twelve month strategy, while it produces handsome returns for the one- and six-month holding strategies. This implies that when it comes to simple returns, some persistence is observed for shorter time intervals but not for the longer twelve month period.

Different results appear when it comes to risk-adjusted alphas. The famous trend applied for excess returns is still present for the one-month holding strategy. Alphas increase as ranking and past returns increase. This is however not the case for the six-month holding strategy, and it completely reverses for the twelve-month holding strategy. It is difficult to make any conclusions based on this because of insignificant alphas for all three procedures. The only 4-factor alpha that sticks out is the spread portfolio when rebalancing every month. It is only significant at the 10% level, but it still creates a signal towards stronger persistence in mutual fund performance for shorter post-formation periods.

Consistency in ranking is illustrated by the charts in section 5.7. Again, large variations between the holding periods can be observed. The evolution of persistent over and under performers is presented as separate probabilities. These are very high for the one-month strategy while they decline substantially when the holding period increases to six months. They are still considered to be at a high level, even though they dropped from approximately 80% to 50% when the holding period changed. These are strong indications of short-term persistence in the sample returns. The story changes once again when the twelve-month holding period is evaluated. Both probabilities close in on the important 25% limit which implies that previous ranking has little to do with future ranking.

More frequent rebalancing clearly changes the overall appearance of the contingency tables. The probability of achieving the same ranking two months in a row is surprisingly high when the portfolios are rebalanced every month. All the paired columns show probabilities over 60% which evidently is a sign of persistent rankings for short periods of time. These columns are also the highest ones when the portfolios are rebalanced every six months, they are however less dominant this time. Another important pattern in this chart is the change in probabilities when the initial ranking is either best or worst. The columns are increasing at an almost constant rate when stepping towards the initial ranking. So it seems fair to conclude that the sample still shows persistent behavior after six months. Next in line are the portfolios that are rebalanced once a year. This chart looks nothing like the other two. All probabilities are now reasonably close to 25%. This indicates that the persistent ranking shown for the previous two cases fades when the holding period increases to twelve months.

Market efficiency in its weak form cannot be rejected on the basis of these observations. Clear patterns in persistent ranking are observed in the contingency tables, but this tells us nothing about the size of the returns that hides behind the columns. This makes them unsuitable to make any general conclusions towards market efficiency. Risk adjusted returns are more practical oriented and serves as a better efficiency indicator. The results are pretty much consistent throughout all the three holding strategies. They imply that no investor could have earned positive risk-adjusted returns if they had implemented one of the strategies presented. All of them are based solely on historic returns, so they are directly aimed towards the weak form of efficiency. It is also worth noticing that potential transaction costs and taxes fall outside these models, so the net returns in real life would have been even smaller. It is therefore fair to say that the market for Norwegian equity mutual funds seems fairly efficient in this context. That being said, there are multiple other ways to check for persistence and market efficiency. Sorting windows and holding periods can for instance be combined in an almost infinite number of ways, so much research can still be done with the same basic approach as the one used in this analysis.

Short-term persistence has been the main focus in this thesis. A short recap of the findings will now serve as a suitable ending to the research. First, funds with high previous returns seem to have relatively higher excess returns for one and six months after the evaluation period. Second, rankings do not significantly affect the risk-adjusted abnormal returns. Third, funds are more likely to achieve the same ranking two periods in a row when the sorted portfolios are rebalanced every one and six months. Fourth and last, persistent behavior in fund returns is gradually diminishing when the post-formation period increases from one to six and twelve months. This goes for simple returns, alphas and rank dependency.

References

Banz, R.W. (1981): “The Relationship between Return and the Market Value of Common Stocks”, *Journal of Financial and Quantitative Analysis,* 14, 421-441.

Bodie, Z., Kane, A. & Marcus, A. J. (2009): *Investments.* Singapore: McGraw-Hill Education.

Brooks, C. (2008): *Introductory Econometrics for Finance,* 2. Edition. Cambridge University Press, UK.

Carhart, M.M. (1997): “On Persistence in Mutual Fund Performance”, *The Journal of Finance,* Vol. 52, No.1 (Mar., 1997), 57-82.

Cochrane, J.H. (2005): *Asset Pricing,* revised edition. Princeton University Press.

Evans, R.B. (2009): “Mutual Fund Incubation”, *Journal of Finance, forthcoming,* available at SSRN: http://ssrn.com/abstract=1005167.

Fama, E.F. (1965): "Random Walks in Stock Market Prices". *Financial Analysts Journal,* 51 (1). September–October 1965.

Fama, E.F. (1969): “Efficient Capital Markets: A Review of Theory and Empirical Work”, *The Journal of Finance,* Vol. 25, No. 2, 383–417.

Fama, E.F., French, K.R. (1993): “Common Risk Factors in the Returns on Stocks and Bonds”, *Journal of Financial Economics,* 33, 3-56.

Fama, E.F., French, K.R. (1996): “Multifactor Explanations of Asset Pricing Anomalies”, *The Journal of Finance,* Vol. 51, No.1, 55-84.

Fama, E.F., French, K.R. (2010): “Luck versus Skill in the Cross Section of Mutual Fund α Estimates”, *Journal of Finance,* 65, 1915–1947.

Hendricks, D., J. Patel and R. Zeckhauser (1993): “Hot Hands in Mutual Funds: Short-Run Persistence of Relative Performance, 1974-1988”, *The Journal of Finance,* Vol. 48, No. 1, 93-130.

Jegadeesh, N. and S. Titman (1993): “Returns to Buying Winners and Selling Losers: Implications for Stock Market Efficiency”, *Journal of Finance,* 48, 65-91.

Jensen, M.C. (1968): “The Performance of Mutual Funds in the Period 1945-1964”, *Journal of Finance,* 23(2), 389 – 416.

Lintner, J. (1965): “The Valuation of Risk Assets and the Selection of Risky Investments in Stock Portfolios and Capital Budgets”, *Review of Economics and Statistics*, 47, 13-37.

Malkiel, B. (1995): “Returns from Investing in Equity Mutual Funds 1971 to 1991”, *The Journal of Finance,* Vol. 50, No. 2, 549-572.

Newey, W. K. and K. D. West (1987): “A Simple Positive Semi-Definite, Heteroskedasticity and Autocorrelation Consistent Covariance Matrix”, *Econometrica,* Vol. 55, 703-708.

Sharpe, W.F. (1964): “Capital Asset Prices: A Theory of Market Equilibrium under Conditions of Risk”, *The Journal of Finance,* Vol. 19, 425-442.

Sørensen, L.Q. (2009): “Mutual Fund Performance at the Oslo Stock Exchange”, *Norges Handelshøyskole.*

Wermers, R. (1997): “Momentum Investment Strategies of Mutual Funds, Performance Persistence, and Survivorship Bias”. *Working paper.*

Ødegaard, B. A. (2011): “Empirics of the Oslo Stock Exchange. Basic, descriptive, results”, *University of Stavanger and Norges Bank.*

French, K.R., retrieved February 22, 2012, http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/index.html

Norges Bank, retrieved January 23, 2012, http://www.norges-bank.no/no/prisstabilitet/rentestatistikk/nibor-effektiv-rente-manedsgjennomsnitt-av-daglige-data/

Oslo Børs, retrieved January 25, 2012, http://www.oslobors.no/ob_eng/markedsaktivitet/stockIndexGraph?newt__ticker=OSEFX&newt__menuCtx=1.6.3

Ødegaard, B. A., retrieved January 22, 2012, http://finance.bi.no/~bernt/financial_data/ose_asset_pricing_data/index.html

Appendix

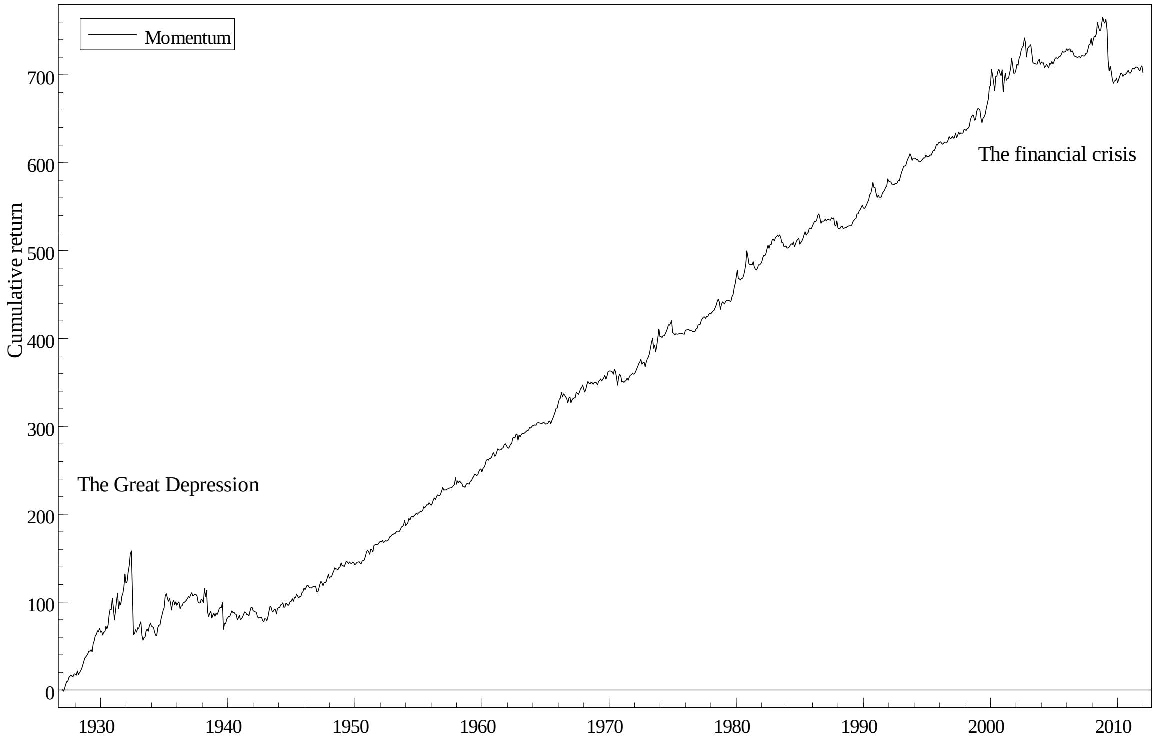

Figure 13: Cumulative returns for the American momentum factor

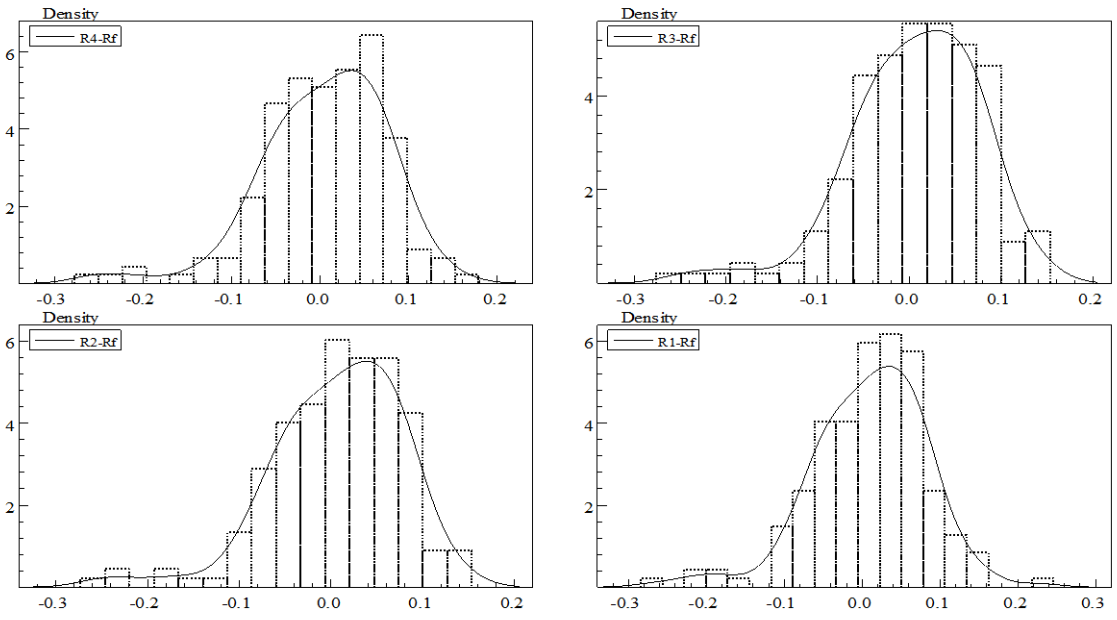

Figure 14: Return distributions for the ranked portfolios based on the one-month holding period

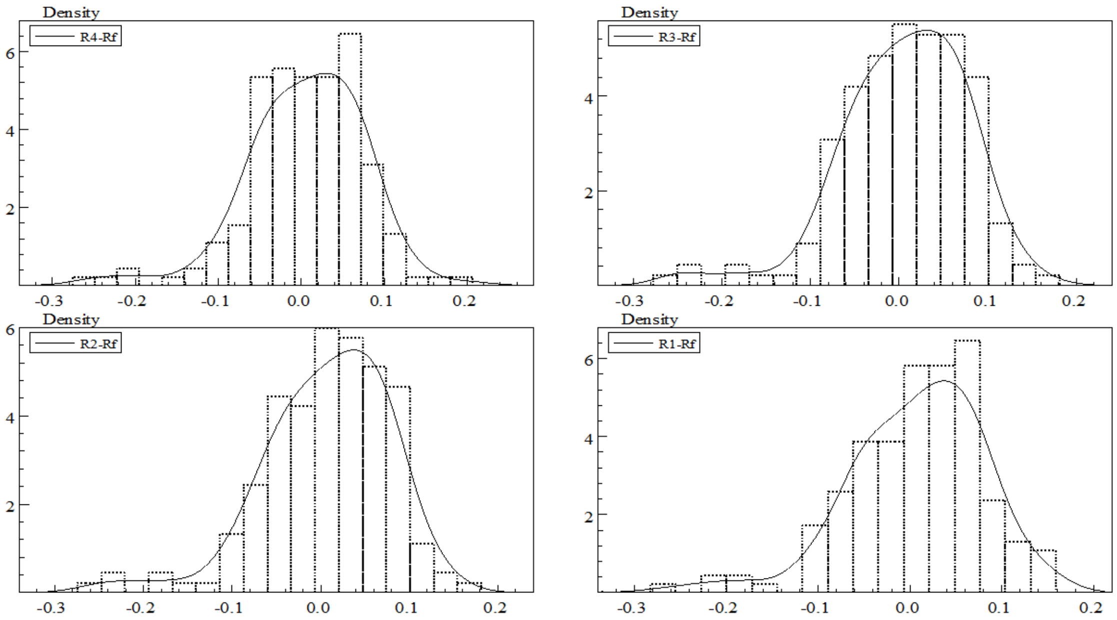

Figure 15: Return distributions for the ranked portfolios based on the six-month holding period

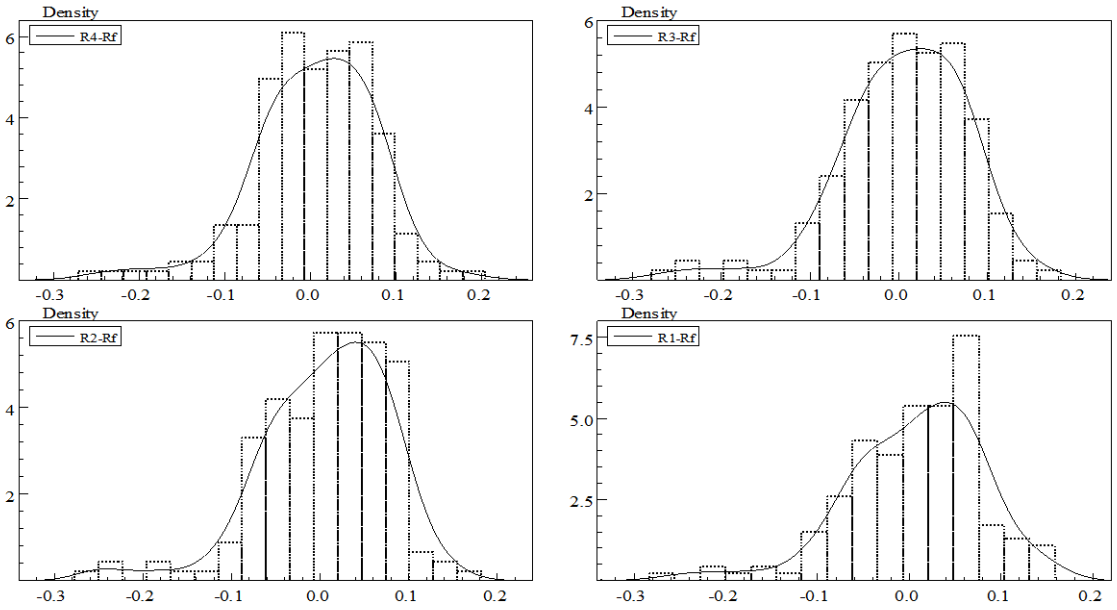

Figure 16: Return distributions for the ranked portfolios based on the twelve-month holding period

Table 9: Portfolios ranked on lagged one-year returns and reformed every month with HAC standard errors

			4-factor model					
Portfolio	Excess return	Std Dev	Alpha	RMRF	SMB	HML	PR1YR	Adj R^2
1 (high)	0,88 %	7,36 %	0,10 %	1,01	0,14	-0,06	0,13	0,93
			(0,70)	(0,36)	(2,56)	(-0,95)	(2,38)	
2	0,68 %	7,03 %	0,04 %	0,97	0,06	0,00	0,03	0,97
			(0,43)	(-2,19)	(2,63)	(-0,06)	(1,64)	
3	0,60 %	7,07 %	-0,05 %	0,98	0,09	0,01	0,01	0,98
			(-0,69)	(-0,72)	(2,69)	(0,58)	(0,72)	
4 (low)	0,43 %	7,07 %	-0,18 %	0,98	0,15	0,03	-0,06	0,96
			(-1,49)	(-0,87)	(3,18)	(0,93)	(-2,12)	

All numbers are based on monthly returns in the time period 1997:01 – 2010:12. The mutual funds are sorted into equally weighted portfolios based on their past twelve-month return. Funds with the highest past returns are put into portfolio 1, while portfolio 4 consists of funds with the lowest returns. Monthly excess returns are regressed against the 4-factor model. RMRF is the excess return on the market proxy. SMB and HML are factor-mimicking portfolios for the size and value effect. PR1YR is a factor-mimicking portfolio for the one-year momentum effect. The t-statistics are in parenthesis below their respective coefficients and the underlying standard errors are heteroscedasticity and autocorrelation consistent (HACSE). All portfolios have the null hypothesis of a RMRF coefficient equal to one, β_1=1.

Table 10: Portfolios ranked on lagged one-year returns and reformed every six months with HAC standard errors

			4-factor model					
Portfolio	Excess return	Std Dev	Alpha	RMRF	SMB	HML	PR1YR	Adj R^2
1 (high)	0,72 %	7,28 %	-0,05 %	1,01	0,16	-0,02	0,11	0,93
			(-0,44)	(0,50)	(2,49)	(-0,54)	(2,30)	
2	0,69 %	7,07 %	0,04 %	0,97	0,07	-0,01	0,03	0,98
			(0,56)	(-1,45)	(3,14)	(-0,40)	(1,75)	
3	0,60 %	7,12 %	-0,02 %	0,98	0,07	0,00	0,00	0,98
			(-0,27)	(-0,99)	(1,99)	(0,10)	(-0,19)	
4 (low)	0,56 %	7,06 %	-0,06 %	0,97	0,14	0,01	-0,04	0,95
			(-0,54)	(-1,07)	(3,03)	(0,23)	(-1,29)	

All numbers are based on monthly returns in the time period 1997:01 – 2010:12. The mutual funds are sorted into equally weighted portfolios based on their past twelve-month return. Funds with the highest past returns are put into portfolio 1, while portfolio 4 consists of funds with the lowest returns. Monthly excess returns are regressed against the 4-factor model. RMRF is the excess return on the market proxy. SMB and HML are factor-mimicking portfolios for the size and value effect. PR1YR is a factor-mimicking portfolio for the one-year momentum effect. The t-statistics are in parenthesis below their respective coefficients and the underlying standard errors are heteroscedasticity and autocorrelation consistent (HACSE). All portfolios have the null hypothesis of a RMRF coefficient equal to one, β_1=1.

Table 11: Portfolios ranked on lagged one-year returns and reformed every twelve months with HAC standard errors

			4-factor model					
Portfolio	Excess return	Std Dev	Alpha	RMRF	SMB	HML	PR1YR	Adj R^2
1 (high)	0,66 %	7,28 %	-0,11 %	1,02	0,18	-0,01	0,10	0,93
			(-0,90)	(0,33)	(2,65)	(-0,22)	(1,76)	
2	0,62 %	7,11 %	-0,03 %	0,99	0,09	0,02	0,00	0,97
			(-0,32)	(-0,81)	(2,28)	(0,79)	(0,01)	
3	0,65 %	7,17 %	0,00 %	0,98	0,06	-0,02	0,02	0,98
			(-0,05)	(-1,11)	(1,81)	(-0,86)	(0,95)	
4 (low)	0,63 %	6,95 %	0,02 %	0,95	0,10	0,00	-0,02	0,96
			(0,21)	(-1,84)	(2,74)	(0,01)	(-0,74)	

All numbers are based on monthly returns in the time period 1997:01 – 2010:12. The mutual funds are sorted into equally weighted portfolios based on their past twelve-month return. Funds with the highest past returns are put into portfolio 1, while portfolio 4 consists of funds with the lowest returns. Monthly excess returns are regressed against the 4-factor model. RMRF is the excess return on the market proxy. SMB and HML are factor-mimicking portfolios for the size and value effect. PR1YR is a factor-mimicking portfolio for the one-year momentum effect. The t-statistics are in parenthesis below their respective coefficients and the underlying standard errors are heteroscedasticity and autocorrelation consistent (HACSE). All portfolios have the null hypothesis of a RMRF coefficient equal to one, β_1=1.